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EXTRACTION OF BEARING FAULT TRANSIENTS FROM A STRONG CONTINUOUS SIGNAL VIA DWPA MULTIPLE BAND-PASS FILTERING

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Abstract: This paper presents a new method to enhance the detection and diagnosis of rolling element-bearing faults based on discrete wavelet packet analysis (DWPA). The extraction of attenuated resonant vibrations due to impacts from localized faults in rolling element bearings is normally achieved by high-pass or band-pass filtering of the vibration signal. The main problem with this approach is the difficulty in choosing an appropriate filter range of interest. This is a serious obstacle when the bearing fault transients are buried in high levels of noise or contaminating signals. An alternative that enables the automation of the selection process and the inclusion of multiple frequency bands of interest is presented. A superior signal to noise ratio is achieved in comparison to either high-pass or band-pass filtering of the signal, as the DWPA feature extraction facilitates the equivalent of automatically selecting an optimal multiple band-pass filter.

Key Words: Adaptive Network-based Fuzzy Inference Systems, Condition Monitoring, Demodulation, Wavelet Analysis, Vibration Analysis

Introduction: The method for the extraction of high frequency transients due to bearing impact resonance is achieved at an optimal time-frequency resolution via best basis discrete wavelet packet analysis (DWPA) representation, using the Daubechies-20 wavelet [1]. Selection of the frequency band or bands of interest is achieved by analyzing the characteristics of the wavelet packets. The selection process is automated through the use of an adaptive network-based fuzzy inference system, thus removing the need for the analyst to manually identify the bands of interest. A superior signal to noise ratio is achieved in comparison to either high-pass or band-pass filtering of the signal, as the DWPA feature extraction facilitates the equivalent of automatically selecting an

optimal multiple band-pass filter. Further enhancement of the signal-to-noise ratio is achieved through hard-thresholding of the wavelet coefficients prior to reconstruction of the final signal. The main limitation of this technique is the increased computational time required over standard filtering approaches, restricting its suitability to signal conditions that are not favorable for standard demodulation due to high levels of contamination from external sources. This constraint should be able to be overcome with the implementation of parallel wavelet based digital signal processors.

This paper briefly introduces the extraction technique implemented, and then examines the performance of the DWPA multiple band-pass filtering for the extraction of a low speed rolling element bearing transient from a strong continuous signal.

Adapative Network Based Fuzzy Inference System (ANFIS): The adaptive network based fuzzy inference system, which is utilized in this investigation for wavelet packet feature extraction, is a transformational model of integration where the final fuzzy inference system is optimized via artificial neural network training. This method of integration was selected due to its ability to incorporate expert knowledge and maintain system transparency, while allowing tuning of the fuzzy inference system via neural training to ensure a satisfactory performance. The validity of the expert knowledge and the suitability of the input data chosen can then be verified by examining the structure and the performance of the final fuzzy inference system. This section describes the design and operation of an adaptive network based fuzzy inference system.

Jyh-Shing Roger Jang introduced the adaptive network based fuzzy inference system (ANFIS) in 1993 [2]. The initial membership functions and rules for the fuzzy inference system can be designed by employing human expertise about the target system to be modelled. ANFIS can then refine the fuzzy if-then rules and membership functions to describe the input-output behavior of a complex system. Jang showed that even if human expertise is not available it is possible to set up intuitively reasonable membership functions and then employ the neural training process to generate a set of fuzzy if-then rules that approximate a desired data set.

Sugeno type fuzzy inferences systems have been used in most adaptive techniques for constructing fuzzy models, due to their more compact and computationally efficient representation of data than the Mamdani or Tsukamato fuzzy systems. A typical fuzzy rule in a zero-order Sugeno fuzzy system has the form:

$$If\ x\ is\ A\ and\ y\ is\ B\ then\ z = c$$

Where A and B are fuzzy sets in the antecedent, and z is a crisply defined function in the consequent. It is frequently the case that the singleton spike of the crisply defined consequent is completely sufficient to cater for a given problem's needs. If required the more general first-order Sugeno can be employed by setting the consequent to $z = px + qy + c$. Higher order Sugeno systems add an unwarranted level of complexity, for minimal remuneration. A zero-order Sugeno fuzzy inference system is used in this

investigation. The equivalent ANFIS architecture for a Sugeno fuzzy inference system is illustrated in figure 1.

input   input   rule   output   weighted   output
        membership   membership   sum
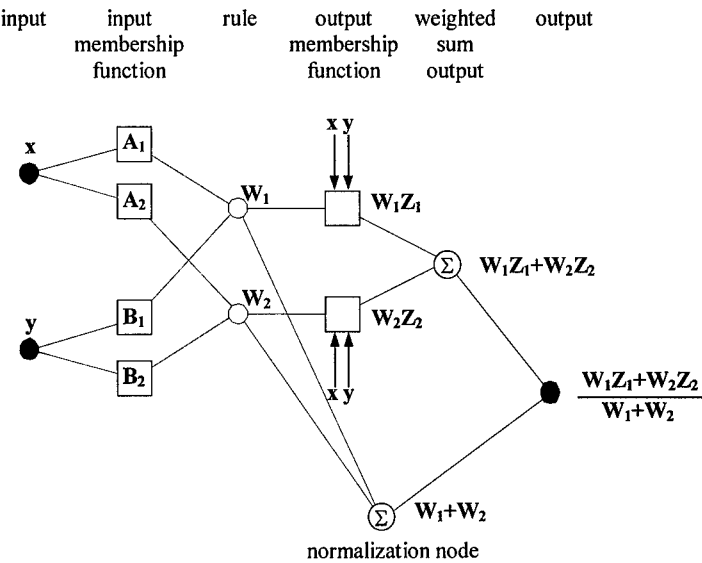   function   function   output

Figure 1: ANFIS zero-order Sugeno fuzzy model

Although any feed forward network can be used in an adaptive network based fuzzy inference system, Jang and Sun implemented a hybrid learning algorithm that converges much faster than training reliant solely on a gradient decent method [3]. During the forward pass, the node outputs advance until the output membership function layer, where the consequent parameters are identified by the least-squares method. The backward pass uses a back propagation gradient decent method to upgrade the premise parameters, based on the error signals that propagate backward. Under the condition that the premise parameters are fixed, the consequent parameters determined are optimal. This reduces the dimension of the search space for the gradient decent algorithm, thus ensuing faster convergence. This hybrid learning system is used in the training of the fuzzy inference systems used for bearing fault feature extraction.

Table 1: LSE-Back propagation Hybrid Learning System

	Forward Pass	Backward Pass
Premise Parameters	Fixed	Gradient Descent
Consequent Parameters	Least-Squares Estimate	Fixed
Signals	Node Outputs	Error Signals

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Implementation of ANFIS for Automatic Feature Extraction: Before training sets are fed into the neuro-fuzzy network, suitable input parameters to train the network must be selected. It is necessary for the parameters chosen to enable the neuro-fuzzy network to make an intelligent extraction of the wavelet packets containing bearing fault related information. The chosen parameters must not only provide a robust foundation for the identification of wavelet packets of interest, but they must also be limited in number so as to avoid the *curse of dimensionality*. This refers to the explosion in the number of rules that occurs when the number of inputs is moderately large. The input parameters that were chosen for this process were kurtosis and the spectrum peak ratio (SPR).

Kurtosis is an effective measure of the spikiness of a signal. A high kurtosis level indicates the wavelet packet is impulsive in nature, as would be expected from a wavelet packet that contains bearing fault related features. Kurtosis is defined as,

$$Kurtosis = \frac{1}{NS_y^4} \sum_{i=1}^{N} \left(y(i) - \mu_y \right)^4 \tag{1}$$

Kurtosis was chosen over other measures of spikiness (crest factor, impulse factor and shape factor) due to its statistically robust nature. A ceiling on the kurtosis values was set at 100, as all values above this are considered exceedingly spiky.

The spectrum peak ratio was defined by Shiroishi [4] as the sum of the peak values of the defect frequency and its harmonics, divided by the average of the spectrum. Shiroishi used the spectrum peak ratio as a trending parameter to indicate the presence of localized bearing defects, which was found to be more robust than considering just the defect frequency.

$$SPR = \frac{N \times \sum_{h=1}^{n} P_h}{\sum_{k=1}^{N} A_i} \tag{2}$$

P_h is the amplitude of the peak located at the defect frequency harmonic, Ai is the amplitude at any frequency, and N is the number of points in the spectrum. In order to differentiate between wavelet packets belonging to different classes of bearing faults, three auto-regressive based peak ratios are employed, spectrum peak ratio inner (SPRI), spectrum peak ratio outer (SPRO) and spectrum peak ratio rolling element (SPRR). Calculation of the spectrum peak ratios was based on Yule-Walker auto-regressive spectral estimates of the signal using a model order of 125, equivalent to one shaft revolution. Removal of outliers in the values of P_h was used to further improve the robustness of this measure.

A total of 2048 wavelet packets were available out of the vibration data collected from a low speed rolling-element bearing test rig. These wavelet packets were individually assessed as to whether they contained bearing related fault features by visual examination of their time series and auto-regressive spectrum. They were then categorized for each fault class as containing fault related features (1), probably containing fault related features (0.66), probably not containing fault related features (0.33), or not containing fault related features (0). The wavelet packet data set included 402 containing inner race

fault defect information, 138 containing rolling element fault information and 64 containing outer race fault information. An additional 762 wavelet packets were created using mathematical models of bearings containing localized faults [5]. The additional wavelet packet data set included 42 containing inner race fault defect information, 83 containing rolling element fault information and 98 containing outer race fault information. The wavelet packets were split into three data sets, a training data set of 1000 wavelet packets, a checking data set of 1000 wavelet packets and a testing data set of 810 wavelet packets.

Given the training and checking input/output data sets, the membership function parameters were adjusted using a back propagation algorithm in combination with a least squares method. The checking data was used to cross-validate and test the generalization capability of the fuzzy inference system. This was achieved by testing how well the checking data fits the fuzzy inference system at each epoch of training, and the final membership functions were associated with the training epoch that has a minimum checking error. This was an important task, as it ensured that the tendency for the fuzzy inference system to over fit the training data, especially for a large number of epochs, was avoided.

Example of Bearing Fault Transient Extraction: The example presented in this paper illustrates the performance of DWPA multiple band-pass filtering for the extraction of bearing fault-related components from a signal principally composed of a continuous sinusoidal signal and its odd harmonics. The example is based on the low speed rolling-element bearing test rig and involves a rolling-element fault of width 0.38mm, an operating speed of 60 rpm and a radial loading of 15 kN.

As depicted in Figure 2, an external signal constructed from a sinusoid (50Hz) amplitude modulated by a low frequency carrier wave at 3Hz clearly dominates the signal. Any transient vibrations due to the bearing fault are well buried by the external signal, with no evidence of a bearing fault apparent when examining the time and frequency (linear and dB) domains.

Digital demodulation is employed in figure 3 in an attempt to isolate bearing fault transients from other signal components present. Figures 3(a+c) illustrate the signal after high-pass filtering at 500Hz and the corresponding enveloped auto-regressive spectrum. The choice of 500Hz for the high-pass filter is based on the theoretical outer race resonance frequency of 696Hz. As the example in question is operating at a low speed (60 RPM) auto-regressive spectral analysis of the enveloped signal is employed. This is due to the relatively short data length (500 points) available after enveloping of the high-pass filtered signal. Although the presence of a rolling-element bearing fault can be ascertained from the demodulated signal, a significant sinusoidal component remains. This is due to the presence of harmonics of the sinusoidal signal above 500Hz, as shown in figure 2(c).
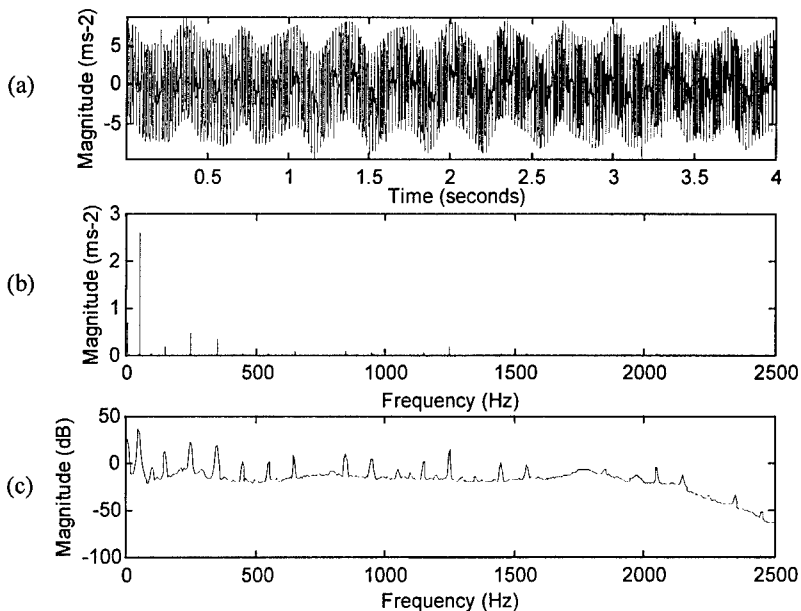
Figure 2: Time domain signal: (a) Continuous sinusoidal signal (50Hz) amplitude modulated by a low frequency carrier wave (3Hz), and a low amplitude rolling-element fault (fault width 0.38mm), (b) Linear FFT, (c) Power Spectral Density.

A band-pass filter was constructed in order to curtail the contamination from the harmonics of the 50 Hz sinusoid. Manual optimization of the filter led to a band-pass filter range of 1500Hz>BPF>2500Hz. As is evident from a comparison of figures 3(a) and 3(b) the band-pass filtered signal results in a much cleaner signal. Unfortunately there is a trade-off, with regions of bearing resonance below 1500Hz being discarded.

DWPA multiple band-pass filtering offers an alternative that surmounts the problem of extracting regions of bearing resonance that are intertwined with continuous signals. Figure 4 illustrates how this method facilitates the extraction of bearing fault-related components from a signal while rejecting the unwanted harmonics. The wavelet packets identified by the adaptive network-based fuzzy inference system as containing bearing fault-related features are indicated. To visualize the rejection of wavelet packets containing unwanted continuous signal components, the power spectral density is plotted along the vertical axis of the DWPA representation. Wavelet packets that contained the harmonic peaks present in the power spectral density plot were rejected by the adaptive network-based fuzzy inference system as containing excessive levels of signal contamination. This clearly demonstrates the ability of DWPA multiple band-pass filtering to extract only the wavelet packets composed predominately of bearing fault-related vibrations.
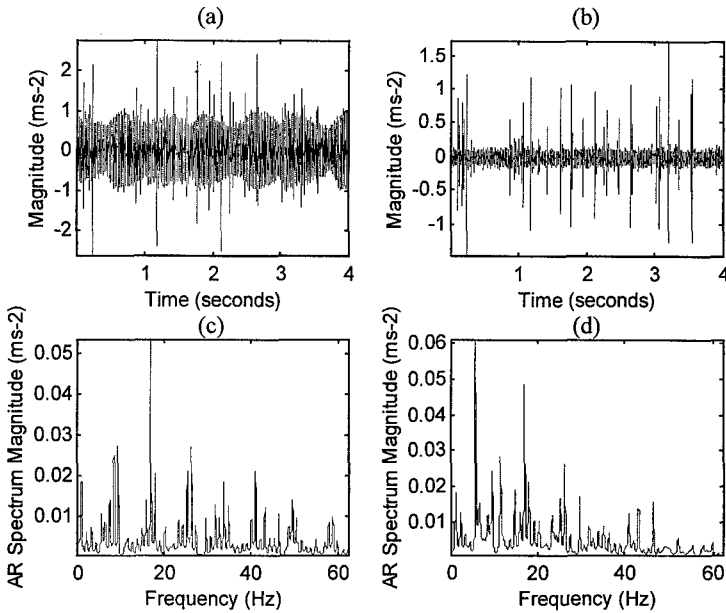
Figure 3: (a) High-pass filtered signal (>500Hz), (b) Best possible band-pass filtered
signal that could be achieved (1500Hz>BPF>2500Hz),
(c+d) The corresponding enveloped AR-spectrum (Yule-Walker, model order 125)

Figure 5(a) depicts the reconstructed signal from the extracted wavelet packets. The
reconstructed signal has a marginally lower level of sinusoidal contamination than the
best possible band-pass filter, and the bearing fault-related transients are also stronger.
This is reflected in the enveloped AR spectra shown in figure 5(c), where the peak at the
rolling-element fundamental fault frequency is more than twice the magnitude of the
corresponding peaks for the high and band-pass filter based spectra (compare figures
3(c+d) with figure 5(c)). Hard threshold de-noising (figures 5(b+d)) almost eliminated
the remaining polluting sources of vibration. This further enhances the ability of DWPA
multiple band-pass enveloped spectra to accurately diagnose the location and magnitude
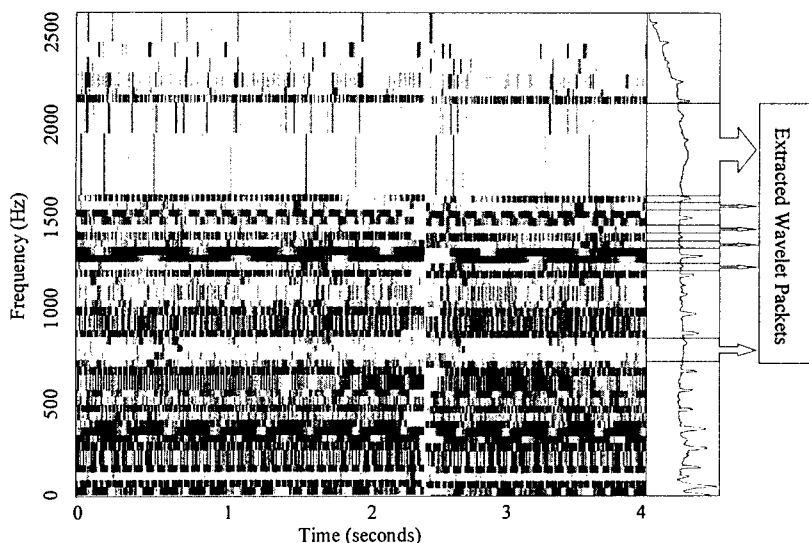of bearing defects.

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Figure 4: DWPA representation of the vibration signal and the wavelet packets selected by ANFIS as containing bearing fault-related components. The extracted wavelet packets are [(3,7)(4,10)(6,17)(6,26)(6,27)(6,30)(6,49)(6,50)(6,53)].

Concluding Remarks: In conclusion, DWPA multiple band-pass filtering performs admirably at the task of extracting bearing fault-related transients from a signal composed predominately of continuous sinusoidal components. This holds true even when unwanted contaminants from continuous components are contained within the bearing's regions of resonance. The adaptive scheme of the DWPA enables the contaminants to be isolated in wavelet packets of high frequency resolution and then discarded by the adaptive network-based fuzzy inference system. This results in the extracted bearing fault signal being relatively untainted by contamination compared to conventional filtering approaches. Used in conjunction with auto-regressive spectral analysis, the technique should provide vastly enhanced diagnostic capabilities compared to standard demodulation for low speed rolling element bearings.
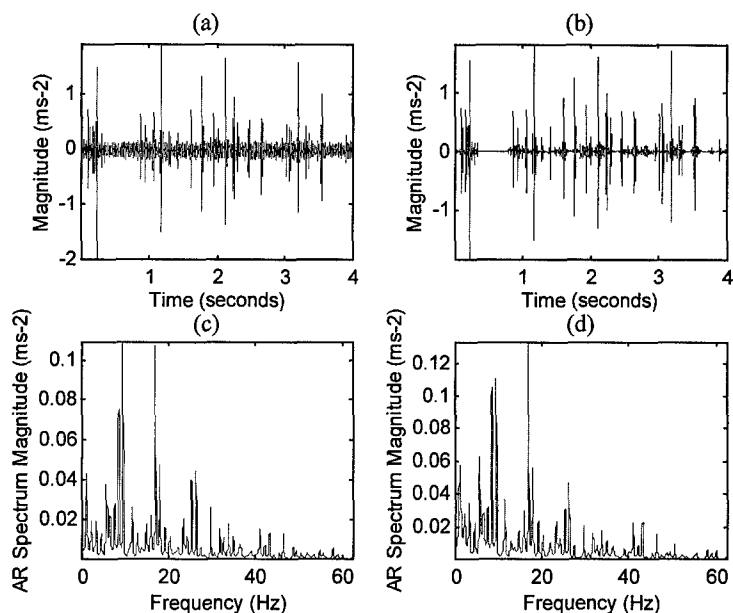
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Figure 5: (a) Reconstruction of extracted wavelet packets,
(b) Hard-threshold de-noised reconstruction of wavelet packets,
(c+d) The corresponding enveloped AR-spectrum (Yule-Walker, model order 125)

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